Peak-Seeking Optimization of Trim for Reduced Fuel Consumption: Architecture and Performance Predictions
Agenda

• Motivation and background
• Description of peak-seeking algorithm
• Implementation on F/A-18
• Performance data flight
• Simulation results
Introduction

• US domestic flights in 2011:
  – 12.1 billion gallons of fuel
  – 114.6 million metric tons of CO₂ equivalent

• NASA’s Environmentally Responsible Aviation project
  – Mitigate the impact of aviation on environment
  – Reduce fuel consumption, emissions, and noise

• Concept presented here:
  – Reduce drag in cruise by altering the trim configuration, applicable to many types of aircraft
Background

• Existing Trim Methods
  – Often scheduled with flight condition
  – Based on a priori information (analytic, wind tunnel, flight data)
  – Differences between models and reality may degrade performance
    • Off nominal flight conditions, lifetime variations, manufacturing differences, external modifications or stores, etc...

• Real-time optimization methods
  – Adaptive Performance Optimization
    • Drag reduction on L-1011 by use of symmetric aileron, (Gilyard et al.)
  – Formation flight
    • Position optimization (Ryan and Speyer)
    • Spanwise lift distribution optimization (Hanson and Ryan)
  – Trim optimization
    • Drag reduction by use of single trailing edge surface group on X-48, in simulation (Griffin et al)
Approach

• Real-time optimization of trim configuration to reduce drag

• Use any number of control effectors

• Utilize onboard measurements of performance, which may be noisy
Peak-seeking Scheme (simplified for 1 effector)

Performance Measurement, \( f \)

Estimated Gradient

Initial Excitation

Command (\( K \times \text{gradient} \))

Command (\( K \times \text{gradient} \))

And so on…

Effector Position, \( x \)

(Commanded by Peak-Seeking Controller)
Peak-seeking algorithm
Assuming the performance function can be treated as linear at any control surface position and expanding to include any number of control effectors, $n$, gives:

\[
\begin{align*}
    f(\bar{x}_k) & \approx f(\bar{x}_{k-1}) + b_k^T (\bar{x}_k - \bar{x}_{k-1}) + O(\bar{x}_k - \bar{x}_{k-1}) \\
    f(\bar{x}_{k-1}) - f(\bar{x}_k) & = \begin{bmatrix} b_{1k} \\ b_{2k} \\ \vdots \\ b_{nk} \end{bmatrix}^T \begin{bmatrix} x_{1k-1} - x_{1k} \\ x_{2k-1} - x_{2k} \\ \vdots \\ x_{nk-1} - x_{nk} \end{bmatrix}
\end{align*}
\]

$F$ and $x$ are measurable, $b_k$ is unknown and to be estimated, and since $F$ and $x$ are noisy and $F$ varies with $x$, a time-varying Kalman Filter is an appropriate choice for an estimator. The states of the Kalman filter are define as the gradient vector:

\[
\zeta_k = \begin{bmatrix} b_{1k} \\ b_{2k} \\ \vdots \\ b_{nk} \end{bmatrix}
\]
Measurement equations are expanded to include multiple previous measurements, M:

\[ \Delta F_k = \begin{bmatrix} f(\bar{x}_{k-1}) - f(\bar{x}_k) \\ f(\bar{x}_{k-2}) - f(\bar{x}_k) \\ \vdots \\ f(\bar{x}_{k-M}) - f(\bar{x}_k) \end{bmatrix}^T \]

\[ H_k = \begin{bmatrix} x_{1k-1} - x_{1k} & x_{2k-1} - x_{2k} & \cdots & x_{nk-1} - x_{nk} \\ x_{1k-2} - x_{1k} & x_{2k-2} - x_{2k} & \cdots & x_{nk-2} - x_{nk} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1k-M} - x_{1k} & x_{2k-M} - x_{2k} & \cdots & x_{nk-M} - x_{nk} \end{bmatrix} \]

Kalman filter measurement equation:

\[ \Delta F_k = \xi_k^T H_k^T + v_k \]

Kalman filter process equation:

\[ \xi_k = \xi_{k-1} + w_k \]

where \( v_k, w_k \) are Gaussian white-noise with covariance matrices \( R_k \) and \( Q_k \) respectively.

A standard linear time varying Kalman filter is then implemented as follows:

\[ K = \hat{P}_k H_k^T \left( H_k \hat{P}_k H_k^T + R_k \right)^{-1} \]

\[ \xi_k = \hat{\xi}_k + K (\Delta F_k - H_k \xi_k) \]

\[ P_k = (I - KH_k) \hat{P}_k \]

\[ \hat{\xi}_{k+1} = \xi_k \]

\[ \hat{P}_{k+1} = P_k + Q_k \]
Persistent Excitation and Initial Excitation

• Persistent Excitation
  – Addition to commanded surface positions that is helical about the trajectory

• Initial Excitation
  – M points around a circle/sphere centered at the initial condition
F/A-18 : NASA 853

- Modified F/A-18 Aircraft - Research flight control computers
- Nonlinear Dynamic Inversion inner loop control laws
- Autopilots:
  - Altitude Hold
  - Airspeed Hold
  - Wing Leveler
- Algorithm adds biases to:
  - Symmetric aileron
  - Trailing-edge flaps
  - Leading-edge flaps

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Performance Data Flight

• Early in development an opportunity was presented to collect performance data during another research activity’s flight.

• Commanded 80 test points with combinations of leading edge flaps, trailing edge flaps, and symmetric ailerons and recorded resulting fuel flow over >30sec per pt.

• Evaluated at a single flight condition of 25,000ft, 240 KCAS
Performance Model

- Developed a new plant model for simulation testing.
- Polynomial fit to flight data across 3 axes
Performance Model

- More detailed data set collected for trailing edge flaps vs symmetric ailerons, leading edge at 5 deg
  - Spanwise lift distribution control

- Baseline
  - Trailing edge flaps, 5 to 6 deg
  - Symmetric ailerons, 0 deg

- Minimum, -2.3%
  - Trailing edge flaps, 3 deg
  - Symmetric ailerons, 5 deg
Noise Model

• Generated a noise model for simulation, added onto output from new performance plant model
New plant model for simulation

• Using new plant model in simulation, peak seeking controller was evaluated and tuned

• Tuning variables:
  – Gain applied to gradient, “controller gain”
  – M, number of previous measurements used by Kalman Filter
  – R and fuel flow filter time constant, tuned for signal noise
  – Q, Kalman filter process covariance
M, previous measurements
Q, R, Fuel flow filter

• Filter on fuel flow time constant and R matrix
  – filter to reduce noise on signal going into Kalman filter, adjust R accordingly

• Q matrix, process covariance, tuned through Monte Carlo type simulation
## Final Tuned Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gain</strong></td>
<td>-105</td>
</tr>
<tr>
<td><strong>M</strong></td>
<td>5 for 2 effectors</td>
</tr>
<tr>
<td></td>
<td>7 for 3 effectors</td>
</tr>
<tr>
<td><strong>Fuel flow filter time average</strong></td>
<td>20 s</td>
</tr>
<tr>
<td><strong>R</strong></td>
<td>$1.85^2 \text{ I}$</td>
</tr>
<tr>
<td><strong>Q</strong></td>
<td>$1.98^2 \text{ I}$</td>
</tr>
</tbody>
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Simulation Results – 2 effector

- Starting from 4 different positions, algorithm converges around -2%
Simulation Results – 3 effector

• 3 effector test, converges to -2.5%
Conclusions

- Peak-seeking algorithm has potential to reduce fuel consumption on wide variety of aircraft types

- Can easily be implemented into existing control structure (assuming ability to actuate multiple effectors, and digital control)

- Algorithm was subsequently flown on 5 flights accumulating about 5 hours worth of test data
  - Results will be presented tomorrow at 5:30pm (Salon J)